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A Game Theoretic Approach for Sustainable Power Systems Planning in Transition

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P A P E R   I N F O

A B S T R A C T

Intensified industrialization in developing countries has recently resulted in huge electric power demand growth; however, electricity generation in these countries is still heavily reliant on inefficient and traditional non-renewable technologies. In this paper, we develop an integrated game-theoretic model for effective power systems planning thorough balancing between supply and demand for electricity markets in transition. In this regard, a Case Study of Iran's power system is used to illustrate the usefulness of the proposed planning approach and also to discuss its efficiency. Sectoral electricity demands of Iran`s power system as nonlinear functions are forecasted by applying times series approach while general information on economical, technological, political and electricity market conditions of sectors is also given. The brief look into the planning results shows that the proposed approach provides not only competitive conditions for renewable technologies expansion but also a robust one compared to the traditional (cost-based) approach.

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1. INTRODUCTION

Over the past three decades, energy systems planning have played an essential role in long-term social, environmental, and economic policy making of developed and developing countries. This issue is especially vital for countries with the on-going economic structure and the significance is self-evident in effective energy systems planning and management. To do so, it is required to bridge the imbalance between electricity supply and demand sectors and incorporate energy sources, conversion technologies, and demand entities into an integrated planning framework. The integrated generation system planning addresses the problem of identifying the most adequate energy sources, expansion size, and timing for generation expansion corresponding to the demand level through the planning horizon. The integrated planning view of power systems is well displayed in several publications. Wouters et al. [1] employed a distributed energy system planning on small residential scale to analyze the impact of energy integration. The results lead to the identification of key components for residential energy systems. The approach developed by Botterud et al. [2] is a real options approach dealing with uncertainty in load growth, and its influence on future electricity prices, which is taken into account in the GEP problem. This approach addresses an electricity price model, where the spot price is a function of load level and installed generation capacity, as well as short-term uncertainties and temporal fluctuations in the market [2]. References [3-6] detail a game theory based (Cournot) model with an exclusive behavior for the purpose of mathematical composition and expression of an integrated GEP problem model incorporating endogenous market prices. For describing the game of GEP problem, the Cournot equilibrium is obtained through iterative methods. Several approaches explicitly recognize price dynamics of demand and supply in certain problem environments. In the case of literature [7], a System Dynamics approach is used to capture the long-run behavior of electricity markets and to characterize the evolution of the electricity prices and the demand. This addresses a feedback mechanism between the individual expansion planning problems

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and the long-term System Dynamics model. Blumberga et al. [8] also showed that system dynamics has a high potential to be used for sustainable end-use energy system planning at both national and sub-sectoral levels. In the case of reference [9], energy system parameters are assumed as fuzzy sets and a fractile-based interval mixed-integer programming (FIMP) method is developed for sustainable municipal-scale energy system planning and management.

The advent of electricity market deregulation has induced a number of important consequences to planning activities of power systems. The most striking consequence of it is to require analyzing long-term market behavior to identify most adequate schedule for generation in terms of growing demand for electricity [10, 11]. This approach caused to emerging integrated models for generation system planning and game theory approach to receive increasing attention from many researchers in this field. The Nash game approach has been extensively applied by power market researchers [12-14]. However, no earlier work has been reported that addresses the issue of how to find game solution if there is interdependency between electricity suppliers` action sets. The pseudo game deal with this issue, so that each player's action affects both the objective function and the feasible action sets of the other players. In this study, an integrated pseudo game-based model is developed in order to effective energy systems planning thorough balancing between supply and demand along the planning horizon.

The remainder of this section is organized as follows. Section 2 is devoted to presenting the research problem. Formulation of the game model is described in section 3. Section 4 explains the execution results of the model development and the comparison results are organized as section 5. The concluding remarks of this study are outlined as the final section (Section 6).

2. GENERATION SYSTEM PLANNING

In generation system planning problem as a traditional optimization model (Equations (1)-(6)), it is assumed that one decision maker makes a long-term strategic plan with perfect foresight, without considering market price and their effects on optimal expansion plan. The objective function can be written as follows and the abbreviations used for the model sets, parameters and variables are shown in Table 1.

$$MinF = \sum_{m=1}^{M} \sum_{t=1}^{T} \left[\begin{array}{l} Vc_t^m . x_t^m . \tau - Ic^m (\sum_{d=0}^{t} Ic^m . y_d^m)^{-b} . \\ y_t^m - \sum_{j=1}^{J} \varepsilon_j . x_t^m . \tau \end{array} \right] . \frac{1}{(1+\delta)^t} \quad (1)$$

where, the constraints of the model include the reserve margin constraint, the limitation of constructions, the technical constraint, and the market penetration rates

constraint. The objective is to minimize the total cost of system over the whole planning horizon and is formulated using three terms. The first term in (1) represents the sum of the operation and fuel costs over the planning horizon. The sum of dynamic investment costs addressing endogenizing technological learning process is formulated as second term in (1).

Increasing knowledge and cumulative application and construction of the technologies lead to reduce the investment costs, and therefore achieve performance improvements over time named technological learning. Learning-By-Doing (LBD) by knowledge accumulation of installer and experiment of a technologies are addressed the diffusion process of a technology. LBD as an important source of information for improving the design characteristics of new technologies and for making these technologies more economical depends on actual implementation of and experimentation with new technologies. Finally, third term in (1) denotes environmental costs associated with selected fuel depending on the electricity production level. The operation, investment, and environmental costs along the horizon are transferred to the initial stage using a discount rate.

TABLE 1. Abbreviations used for model sets, parameters and variables

Indices	
j	Input fuel, j=1,2,…, J
t	Stage in the planning horizon (year), t=1,2, …, T
T	Number of stages in the planning horizon
g	Time period, g=t-f,….,t
d	Time period, d= 0,1,…,t
m	Supplier (technology) number, m=1,2,3,…., M
Parameters	
b	Technological learning rate
p_t	Electricity price in stage t (1000Rial /MWh)
Vc_t	Operation costs in stage t (1000Rial /MWh)
Ic	Investment costs (1000Rial/MW)
ω_t	Utilization factor (%)
ε_j	Environmental cost coefficient of fuel j (1000Rial/MWh)
f	Technical life (Year)
φ	Increment activity (%)
Mc_t	Maximum allowed capacity expansion in stage t (MW)
δ	Discount rate (%)
C_0	Existing capacity (MW)
τ	Number of hour in a year (hour)
F	Total expected profit
Decision Variables	
x_t	Assigned capacity for production in stage t (MW)
y_t	Installed capacity in stage t (MW)

Reserve margin constraint

The Reserve Margin (RM) is a network security indicator that planners often use to assess the robustness of a generation system purely from a capacity point of view. It corresponds to the surplus of installed capacity regarding the peak load demand for each stage of planning horizon according to Equation (2).

$$RM_t = \left(\text{Assigned capacity - Peak load} \Big/ \text{Peak load} \right) \cdot 100\% \quad (2)$$

The total power output generated by all technologies must not be less than the sum of total power demand and its Reserve Margin (*RM*) according to Equation (3).

$$D_t .(1 + RM_{min}) \le \sum_{m=1}^{M} x_t^m \quad t = 1,2,...T \quad (3)$$

Limitation of constructions

Inequality (4) represents the limits set for the capacity to be added in each stage for m^{th} technology. The construction time of the new technologies, proportional to their types, practically restricts the number of units selected to build during a planning interval. This constraint is expressed the limitation of constructions:

$$y_t^m \le Mc_t^m \quad t = 1,2,...T \quad m = 1,2,...M \quad (4)$$

Technical constraint

Constrain (5) enforces that the assigned capacity in each stage should not be exceed accumulated capacity over the planning horizon for each technology:

$$x_t^m \le \omega_t^m \sum_{g=t-f}^{t} y_g^m + C_0^m , t = 1,2,...T \quad m = 1,2,...M \quad (5)$$

Market penetration rates constraint

Finally, flexible dynamic constraint (6) is used for limiting activity of installed capacity available during time period *t* based on its activity during the previous time period, (*t-1*). Simply speaking, this constraint limit how quickly the activity of a technology can increase or alternatively how steeply the activity can decline between two time periods.

$$-\varphi \le x_t^m - x_{t-1}^m \le \varphi \quad t = 1,2,...T \quad m = 1,2,...M \quad (6)$$

The main purpose of developing this model is that using its results as exogenous market prices of our proposed model. We use the marginal costs of the system as initial market prices (p_t). These prices are obtained by the dual values corresponding to the energy demand constraints for each stage.

3. GAME-THEORETIC STATEMENT OF PROBLEM

The game models dealing with production competition are due to Cournot [15]. This approach is modeled on Nash–Cournot equilibrium, wherein players (subsystems) make simultaneous decisions in relation to the quantities to be produced. The players are characterized by ability to anticipate their impacts on the market through the knowledge of the inverse demand curve.

Simultaneous non-cooperative (Nash) game theory involves multiple decision-makers and sees participators as players who act independently without collaboration or communication with any of the others. However, in a non-simultaneous non-cooperative (Stackelberg) game, one player as leader can act before the other and the strategies of followers must be determined based on leader strategy.

According to Figure 1, we propose an integrated game-based modeling framework including Supply, Coordination, and Demand levels. A Stackelberg game consisting of a leader i.e., Independent System Operator (ISO), eleven followers (supplier) and four non-Stacklberg followers (demand entities) is developed in the supply and coordination demand levels, however a sub game Nash-Cournot model is used to find the best solution of each follower for decision-making of generation expansion in the supply level.

In pool markets, the ISO (leader) makes decision about market price (*p*) prior to the decisions of the supplier (followers) at the lower level about amount of generation. Afterwards, the followers make their decisions while they compete to each other. The decisions of the followers are made taking into consideration the leader' and the other followers' decisions, besides, each player's strategy is depended on the feasible action sets of the other followers considering the reserve margin constraint.

Since a follower competes against other followers, the lower-level problem forms a Nash-Cournot game parameterized in terms of the leaders' decisions. In case of a single leader, the problem is stated as a Mathematical programming with equilibrium constraints (MPEC) optimization problem. MPEC is the study of constrained optimization problems where the constraints include variational inequalities or complementarities (i.e., the reserve margin constraint).
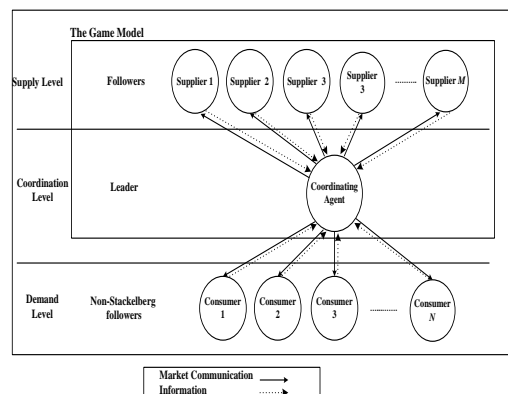

Figure 1. The proposed integrated modeling framework

3. 1. Followers' Problem To formulate the followers' problem, we assume that there are M self-interested players participating in the electricity market under study, each of them solving optimization problem (7), which is a reformulation of problem (1)-(6) incorporating market price variable as follows:

$$Max\lambda^m(x(t)^m, y(t)^m, X^{-m}, p) =$$

$$\sum_{t=1}^{T}\begin{bmatrix} p(t).x(t)^m.\tau - Vc(t)^m.x(t)^m.\tau - \\ Ic^m(\sum_{d=0}^{t} Ic^m.y(t)^m)^{-b}.y(t)^m - \sum_{j=1}^{J}\varepsilon_j.x(t)^m.\tau \end{bmatrix}\cdot\frac{1}{(1+\delta)^t}$$

$$s.t : x(t)^m \in \Psi^m(X^{-m})$$

$$y(t)^m \leq Mc(t)^m \quad t = 1,2,...T \quad m = 1,2,...M$$

$$x(t)^m \leq \omega(t)^m \sum_{g=t-f}^{t} y(g)^m + C_0^m , \quad t = 1,2,...T \qquad (7)$$

$$m = 1,2,...M$$

$$\sum_{t=0}^{T} y(t)^m \leq Ac^m , \quad m = 1,2,...M ,$$

$$-\varphi \leq x(t)^m - x(t-1)^m \leq \varphi , t = 1,2,...T , m = 1,2,...M$$

where the model includes the reserve margin, the limitation of constructions, the technical, and the market penetration rates constraints. X^{-m} denotes all the players' strategies except for player m and $\Psi^m(X^{-m})$ is represented for the strategy space of player m.

The objective of this problem is to maximize the profit of player m along the planning horizon.

3. 2. ISO's Market Clearing Problem The objective of this problem (π) is to minimize the absolute deviation between the total demand and the total supply in percentage as follows. The decision variable $z(p)$ is the total supply at stage t that depends on the market price.

$$Min\pi(z(p)) = \left| (D(t).(1+RM) - z(p))\Big/ D(t).(1+RM) \right| \qquad (8)$$

$$s.t.: \quad z(p) \in \theta(p)$$

where, $z(p) = \sum_{m=1}^{M} x(t)^m$ and $\theta(p)$ denotes the solution set provided by solving the followers' problems. Pereira and Saraiva [7] using System Dynamics approach illustrated market price variation of period t which is formulated based on the deviation between the total demand and the total amount of generation of period t, and also an attenuation factor to smooth eventual large deviations between demand and generation as follows:

$$p(t) = p_0(t) + p_0(t).\psi.$$

$$\left((D(t).(1+RM) - z)\Big/ D(t).(1+RM)\right) \qquad (9)$$

where, $p_0(t)$ and ψ are named positive demand parameters [16]. Given Equation (9), the Pseudo Game

Model for Iran`s Power System (PGMIPS) model is an MPEC model that is formulated as follows :

$$Max\lambda^m(x(t)^m, y(t)^m) =$$

$$\sum_{t=1}^{T}\begin{bmatrix} p(t).x(t)^m.\tau - Vc(t)^m.x(t)^m.\tau - \\ Ic^m(\sum_{d=0}^{t} Ic^m.y(t)^m)^{-b}.y(t)^m - \sum_{j=1}^{J}\varepsilon_j.x(t)^m.\tau \end{bmatrix}\cdot\frac{1}{(1+\delta)^t}$$

$$D(t).(1+RM(t)) \leq \sum_{m=1}^{M} x(t)^m \quad t = 1,2,...T \quad y(t)^m \leq Mc(t)^m$$

$$\qquad (10)$$

$$t = 1,2,...T , \quad m = 1,2,...M , x(t)^m \leq \omega(t)^m \sum_{g=t-f}^{t} y(g)^m + C_0^m$$

$$t = 1,2,...T \quad m = 1,2,...M \quad -\varphi \leq x(t)^m - x(t-1)^m \leq \varphi$$

$$t = 1,2,...T \quad m = 1,2,...M$$

where, the coupled reserve margin constraint, determine the feasible set or strategy space of player m. Given the reserve margin constraint as a variation inequality, it is necessary to apply some very specific search techniques (i.e., decomposition methods) with good understanding of the structure of the problems in order to find solutions. A decomposition method i.e., Gauss-Seidel algorithm (described below) which is most popular among practitioners [17] is chosen to solve the intended pseudo game problem.

In the proposed integrated framework, the intended Stackelberg game model is utilized as follows: the leader (ISO) initializes the Market Clearing Prices (MCPs) through the planning horizon and submits them to the followers (supplier) and non-Stacklberg followers (demand entities). Using these MCPs, non-Stacklberg followers adjust their demands (actions) and followers update their plans and resubmit them (supply strategies). The supply plans are aggregated and compared to the total demand level (received from non-Stacklberg followers) in order to calculate the required price change, clear the market price, and determine the MCPs by leader. Afterwards, signals under the form of modified MCPs are sent to the supply and demand levels. This iterative process is repeated until the required price change is less than amount allowed by leader, hence, market equilibrium condition will be satisfied through the planning horizon and the current MCPs are equilibrium prices or final MCPs.

Step 1 (Coordination level): Assume **p** is the length T vector of the MCPs. Initialize the MCPs as ($\mathbf{p}^{k=0}$) based on the dual values of problem (1)-(6) and start from first stages ($t = 1$).

Step 2: Set game counter k=0.

Step 3 (Demand level): Initialize exogenous demand vectors ($d_n^0, \forall n \in \{1,2,....,N\}$) based on received $\mathbf{p}^0$ (The more detailed description is provided in section 2). For each game repetition of period t, select a demand modification action in terms of $\mathbf{p}(t)^k$ (received from leader) using the coefficients of price elasticity of demand according to Equation (11a).

$$d_n(t)^k = d_{\mathrm{mod}\,n}(t)^k \cdot (\mathbf{p}(t)^k / \mathbf{p}^0(t))^{e_n} + d_{\mathrm{mod}\,n}(t)^k \qquad (11a)$$

$$d_{\mathrm{mod}\,n}(t)^k = \left(\frac{(d_n(t)^0 - d_n(t-1)^0)}{d_n(t-1)^0}\right) \qquad (11b)$$

$$\cdot d_n(t-1)^k + d_n(t-1)^k$$

It should be noted that the modified initial demand of period t ($d_{\mathrm{mod}\,n}(t)^k$) is calculated in terms of final demand of previous period ($d_n(t-1)^k$) and its initial change percentage ($(d_n(t)^0 - d_n(t-1)^0)/d_n(t-1)^0$) according to Equation (11b) in order to incorporate dynamics of demand. Initial change percentage of demand is change percentage of exogenous demands (in terms of previous period demand) for each period. Besides, $d_{\mathrm{mod}\,n}(t)^k$ is modified in terms of $\mathbf{p}(t)^k$ according to Equation (11a) in order to incorporate price dynamics of demand.

Step 4 (Supply level): Update profit function $\lambda_m^{\,k}, \forall m \in \{1,2,....,M\}$ for each followers in terms of $\mathbf{p}(t)^k, \forall t \in \{t = 1,2,..,T\}$ according to Equation (7). Introduce the investment plan of follower m for kth game repetition as $S_m^{\,k}$.

Step 5 (Coordination level): Determine $\mathbf{D}(t)^k$ and $\mathbf{S}(t)^k$ by adding up the $d_n(t)^k$ s and $S_m^{\,k}$ s, respectively. Afterwards, calculate $\Delta\mathbf{p}(t)^k$ as follows:

$$\Delta p(t)^k = \psi \cdot \mathbf{p}(t)^k \left[\frac{\mathbf{D}(t)^k(1+RM) - \mathbf{S}(t)^k}{\mathbf{D}(t)^k(1+RM)}\right] \qquad (12)$$

If $\Delta\mathbf{p}(t)^k$ is more than θ_{AV} go to step 6, otherwise set t equal to $t+1$, substitute $\mathbf{p}^k$ for $\mathbf{p}^0$ and go to step 2 while $t<=T$ is met. If t is greater than T, stop algorithm and return $\mathbf{p}^k$ as final MCPs.

Step 6 (coordination level): Set k to $k+1$. Modify $\mathbf{p}(t)^{k+1}$ in terms of the price mismatch ($\Delta\mathbf{p}(j)^k$) according to Equation (13a) where the initial required price change ($\Delta\mathbf{p}(j)^0$) is assumed zero. Afterwards, adjust $\mathbf{p}^{k+1}$ dynamically as an autoregressive time series based on the modified $\mathbf{p}(t)^{k+1}$ according to Equation (13b) and go to step 3.

$$\mathbf{p}(t)^{(k+1)} = \Delta\mathbf{p}(t)^{(k)} + \mathbf{p}(t)^{(k)}$$
$$\mathbf{p}(h) \leftarrow 0.36\mathbf{p}(h-1) + \mathbf{p}(h) \quad \text{h= t+1,..,T} \qquad (13)$$

According to Equation (13b), the price values of next periods are adjusted dynamically (as an autoregressive time series) in terms of their previous period value ($0.36\mathbf{p}(h-1)$) and their present value ($\mathbf{p}(h)$) when a change is applied to the price value of present period.

4. THE EXECUTION RESULTS

In order to show the applicability and the efficiency of this framework, we developed it based on a case data named, SAIPS (Simulated Agents of Iran`s Power System). The proposed integrated game model was developed for a 30-year horizon (T=30) from 2015 to 2044 considering eleven candidate technologies (including renewable and non-renewable) and four electricity-consuming sectors. In this study, we assume the discount factor δ equal to %12, the learning rate b equal to 0.21, the increment activity φ equal to %38, the coefficient of price elasticity of demand entities e equal to - 0.7, and the attenuation factor ψ equal to %70 (Management and Economy of Electric Power Group, 2011). Two main phases of the study were future electricity demands forecasting (as initial demand values) and developing the model based on the solution algorithm mentioned in section 3.

The exogenous Electricity Demands

Forecasting the future electricity demands is the main phase in generation expansion planning process. To incorporate long time causal relationships, autoregressive with exogenous regression components models have received increasing attention from many researchers in the field of peak demand forecasting. Some recent studies have found evidences that nonlinear functions outperforms over linear ones for explaining the behavior of long-term electricity demand [18]. We proposed ARIMAX (Autoregressive Integrated Moving Average with Exogenous Inputs) model in order to forecast *nonlinear* peak demand function of Iran`s power sectors (residential, commercial and public services, industrial and agriculture).

To find the most parsimonious model, all plausible model structures must be developed and examined in terms of the complexity and goodness of fit. Data transformation of the response series and their exogenous regression components leads to violation of classic regression assumptions. Hence, nonlinear optimization techniques (e.g., Gauss-Newton) are used to estimate the ARIMAX model parameters. For instance, Tables 2 shows the results of model selection process of industrial peak demand using Gauss-Newton algorithm. The results of Table 2 is interpreted as conditional mean of log (Yind) depends on: one past observation (Yind (t-1)) with coefficient of -0.0461; three past innovations ($\varepsilon_{t-1}, \varepsilon_{t-2}, \varepsilon_{t-3}$) with coefficients of -0.2119, -0.0105, and -0.0127; and five exogenous variables (Log Nco, Iec, Tps, Diff Iet, VGRI) with coefficients of 0.2445, 9.54e-006, -0.0067, -0.0008, 0.00061. Moreover, conditional variance of log (Yind) depends on two lagged squared innovations ($\varepsilon^2_{t-1}, \varepsilon^2_{t-2}$) with coefficients of 0.1460, 8.87e-021.

Phase 3: Performance Evaluation: To select the best fitted model for forecasting, it is required to assess the predictive ability of all plausible models.

It is recommended to use cross validation to evaluate out-of-sample forecasting ability in order to overcome over-fitting problem. Dividing response series into training and validation sets, fitting a model based on training data, and assessing the forecasts of validation set in terms of Prediction Mean Square Error (PMSE) and Akaike`s Final Prediction Error (FPE) measures are cross validation phases. PMSE measures the discrepancy between model forecasts and actual data as follows:

$$PMSE = \frac{1}{M} \sum_{i=1}^{M} (y_i - \hat{y}_i)^2 \qquad (14)$$

where, M represents the number of validation data, denoted y_i, i=1, 2, 3,…, M and $\hat{y}_i$ stands for forecasts. FPE statistic includes two terms, the sum of the residuals for the validation data set and a complexity penalty term that increases as the number of parameters in the model grows. The general FPE formula considering a Sum-of-squares Error (SSE) is developed as follows:

$$FPE = \frac{SSE \cdot (n+1)(n+p)}{n \cdot (n-p)(n-p-1)} \qquad (15)$$

where n stands for number of observations and p is number of estimated parameters.

In this assessment, we used the first 21 observations (from 1990 to 2008) as training data to estimate the model, and then forecasted the next 3 periods (2009 to 2011) as validation data. The results of the predictive performance checking based on PMSE and FPE for the industrial peak demand (as an example) are provided as Table 2.

Phase 4: Forecasts development: By using the model selected in previous phase forecasts can be developed over a future time horizon (2015 to 2044). Also, the forecasts of Iran`s industrial, residential, services, and agriculture peak demand up to 2044 in business-as-usual condition were determined.

5. THE COMPARISION RESULTS

In order to illustrate how incorporating the system dynamics, deregulation of the electricity prices and inducing the technological change will influence the generation expansion decisions, we compared the results of the SAIPS model to the results of the cost-based optimization model (Figure 2).

In cost-based optimization model, it is assumed that the decision maker makes a long-term strategic plan with perfect foresight, without considering the inter-temporal dynamics of market price, the demand-side interactions, and their effects on the optimal expansion plan.

TABLE 2. The results of model selection process of industrial peak demand

	Log (Yind)	Exogenous Series				
		Log Nco	Diff Iet	VGRI	Tps	Iec
Specified Structure	ARIMAX(1,3,5)/ GARCH(0,2)	ARIMA (1,4)/ GARCH(0,2)	ARIMA(4,3)/ GARCH(1,1)	ARIMA (1,7)	ARIMA (5,3)/ GARCH(1,1)	ARIMA (1,1)
Coefficients	C= 3.2103 AR(1)= -0.0461 MA(1)= -0.2119 MA(2)= -0.0105 MA(3)= -0.0127 Log Nco = 0.2445 Iec = 9.54e-006 Tps = -0.0067 Diff Iet = -0.0008 VGRI=0.00061 K= 1.95e-005 ARCH(1)= 0.1460 ARCH(2)= 8.87e-021	C= 0.0432 AR(1)=1 MA(1)= 0.8670 MA(2)= 0.8049 MA(3)= 0.1884 MA(4)=-0.0066 K= 0.0001 ARCH(1)= 1 ARCH(2)= 5.61e-021	C= 10 AR(1)= -0.6863 AR(2)= -0.5643 AR(3)=-0.2131 AR(4)= 0.5262 MA(1)=1.3617 MA(2)= 1.3617 MA(3)= 1 K= 2e-007 GARCH(1)=0.9783 ARCH(1)= 0	C = 15.795 AR(1)=0.4160 MA(1)=-0.5469 MA(2)= -0.1106 MA(3)=0.7399 MA(4)=-0.7472 MA(5)=-0.2935 MA(6)= 0.3008 MA(7)= -0.3423 K= 43.845	C=0.3624 AR(1)= -0.3461 AR(2)=0.3276 AR(3)=0.3735 AR(4)=0.4120 AR(5)=0.0189 MA(1)=2.2294 MA(2)= 1.8779 MA(3)= 0.5108 K= 0.00907 GARCH(1)=0 ARCH(1)= 2.1815	C= 1437.6 AR(1)= 1 MA(1)= - 0.0315 K= 9.46e+006
# of Interation	52	57	63	46	58	22
p	13	9	11	10	12	4
PMSE	2.14E-04	1.53E-04	7.07E+00	4.38E+01	1.04E-01	4.38E+01
FPE	4.06E-04	3.08E-04	1.66E+01	9.54E+01	2.98E-01	6.16E+01

However, the SAIPS model, suggests a policy of supply corresponding to the endogenized peak demands and to the reserve margin interval of interest. As seen, both the supply and endogenized peak demand levels in this model have similar evolutions reflecting the fact that capturing demand dynamics in the system leads to a realistic demand values.

In cost-based optimization model, the total supply plan is developed in terms of long-term forecasted peak demands and exogenous electricity prices while they address uncertainty, hence, the related reserve margin evolution displays a rough fluctuations according to Figure (3). The steady behavior of the reserve margin in the SAIPS model is a result of handling uncertainty in the demand and market price values. As seen, the mechanism of inter-temporal modification of market prices and incorporating the demand-side interactions in the SAIPS model lead to not only an economical supply plan but also a reliable one.

As mentioned before, the cost-based optimization model was developed aiming at determination of the dual values of the problem as the initial market prices.
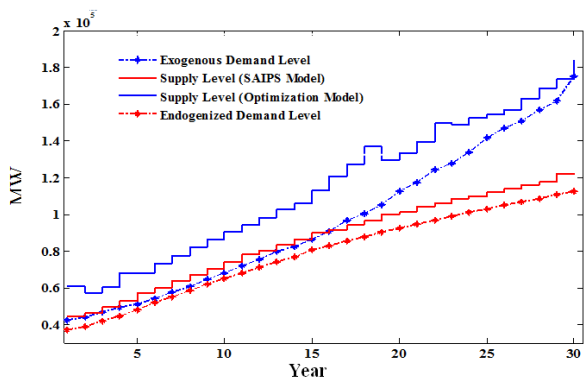
These dual values correspond to demand constraint of exogenous demand for each stage of the planning horizon; however, long-term demand forecasts in uncertain problem environments can lead to unreliable results.

Considering the initial surplus/shortage trend, the evolution of MCP in the planning horizon for the cost-based optimization and the SAIPS models is demonstrated in Figures (4a) and (4b), so that the amount of surplus/shortage is calculated for each period of comparison between the optimization model`s supply level and the level of $(1+RM)*D_t$.

In cost-based optimization model, the solution is achieved without considering market dynamics and the effects of demand side interactions on investment plans. However, the SAIPS model tries to keep equilibrium in market incorporating market dynamics as Equation (13) and also system interactions by algorithm iteration. The two-side structure of SAIPS model causes that the amount of surplus/shortage calculated by coordinating agent to affect not only generation expansion decisions, but also demand level. Thereby, it leads to the decrease of demand level while the surplus exists and the MCP increases. To add up, it can be concluded that the MCPs of the SAIPS model remain relatively low because of modifications of demand and supply levels in terms of market price changes.

The Expansion Plan of Renewable/Non-renewable Technologies

In this subsection, the technology capacity expansion plan of the proposed model is compared to that of the cost-based (traditional) model. The traditional model assumes that the decision maker makes a long-term strategic plan with perfect foresight, without considering the inter-temporal dynamics of price and demand and their effects on the optimal expansion plan.

Figure 2. The supply and demand evolutions of the SAIPS and the cost-based optimization models along the planning horizon
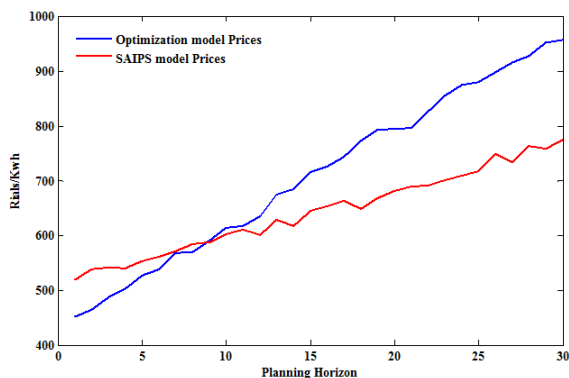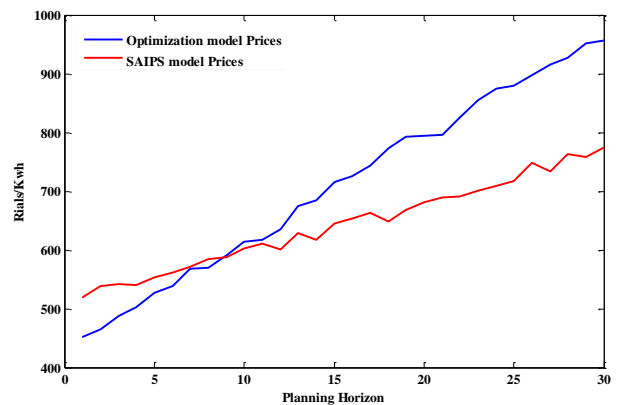

Figure 3. The reserve margin evolutions of the SIAPS and the cost-based optimization models along the planning horizon

Figure 4a. The evolution of the MCP of the cost-based optimization and SAIPS models along the planning horizon
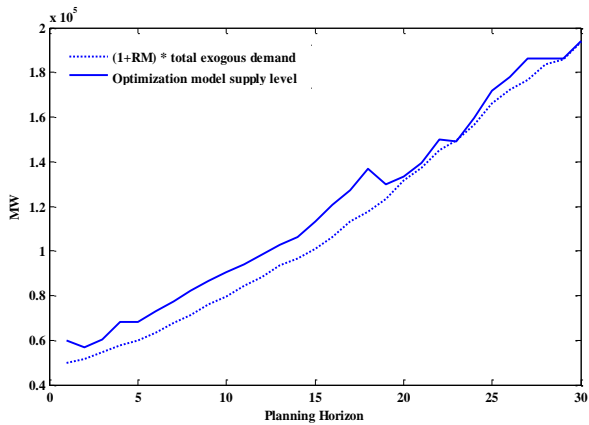
Figure 4b. The evolution of the surplus/shortage corresponding to the cost-based optimization model supply level and the level of $(1+RM)*D_t$

According to Figure 5, the traditional model results indicate that the optimal decision is that to install 5 combined-cycle units in 2011 and then 12 units during 2012 to 2014 as well as one gas-based unit in 2014 responding to the network demand.

The combined-cycle technology has the highest investment share among the fossil fuel based technologies. The gas-based technology takes the second place in the optimal capacity expansion plan due to having low operation and maintenance costs and the ability of co-producing electricity and thermal energy.

Regarding the stringent political conditions and sanctions in the first decade of the plan, investment by the coal-based technology is deferred to the period 2016-2019. Causing no pollution and having low operation and maintenance costs, the hydroelectric technology, with the initial capacity of 87 units, will be invested on annually until the year 2027. It is noteworthy that with respect to the learning mechanism of technologies and the reduction of investment costs in the third decade of the plan, the solar thermal and photovoltaic technologies will have the ability to compete with mature technologies.

In the second decade of the plan, as the equipment's technical lifetime draws to a close and existing capacities decrease, the electricity suppliers are stimulated to invest according to Figure 6. The relatively considerable decrease of demand levels in the proposed model can be observed using competitive prices and incorporating the price dynamics of demand, so that in the first few years, the capacity expansion of the technologies is not planned due to the existing capacities in the gas, the steam and the hydroelectric technologies and also the decreased demand level, in order to meet the mild growth of demand over this period.

The highest shares of the capacity expansion belong to the combined-cycle and steam technologies, which have high performances and relatively low investment and production expenses.
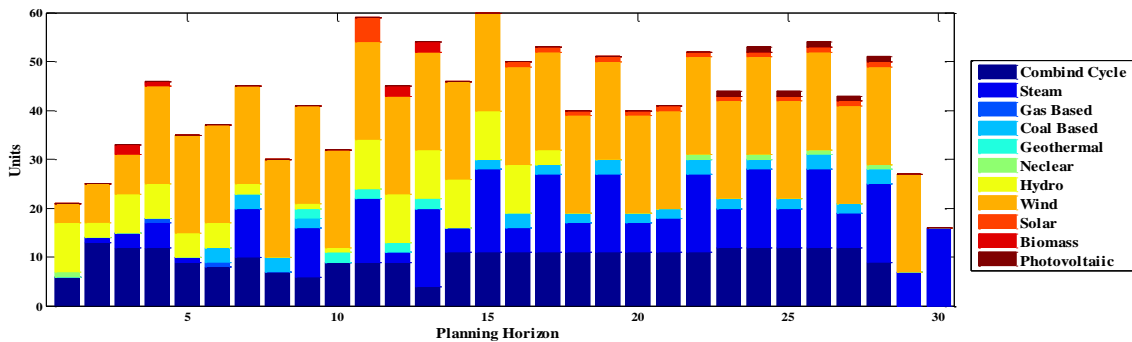

Figure 5. The expansion plan of the renewable/non-renewable technologies along the planning horizon (The cost-based optimization model)
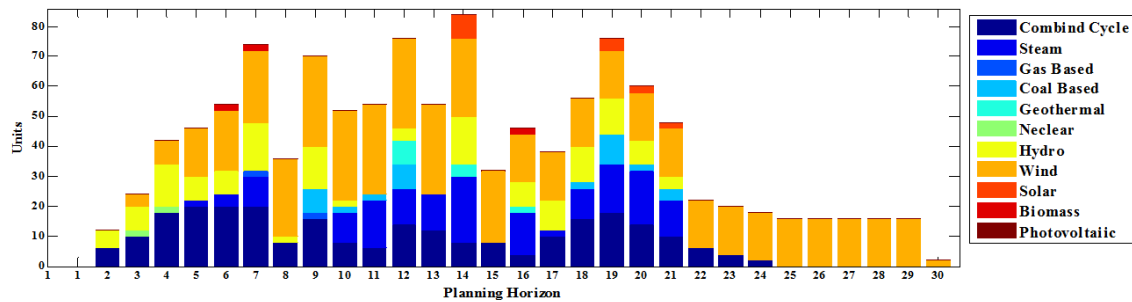

Figure 6. The expansion plan of the renewable/non-renewable technologies along the planning horizon (The proposed model)

6. CONLUSIONS

In this paper, an integrated (pseudo) game model was developed for sustainable power systems planning thorough balancing between supply and demand in transition. This framework helps energy system planners to develop more sustainable and economical generation expansion plans under a good understanding of market behavior.

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A Game Theoretic Approach for Sustainable Power Systems Planning in Transition

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PAPER INFO	چکیده

در بازارهای انرژی، رقابت بر روی قیمت و کمیت می‌تواند به عنوان انگیزه‌ای در جهت توسعه بخش انرژی پایدار استفاده شود، و همچنین میتواند استفاده از منابع انرژی تجدید پذیر را افزایش دهد و در سمت عرضه و تقاضا کارایی انرژی را بهبود بخشد. بر همین اساس لازم است با درک درستی از مسائل مذکور سیستم پشتیبانی تصمیم گیری قابل اطمینانی برای برنامه ریزی توسعه تولید پایدار ایجاد شود. اخیرا" در این زمینه مدل‌های مبتنی بر نظریه بازیها به عنوان ابزارهای پشتیبانی تصمیم گیری توجه روزافزون محققان بسیاری را به خود جلب کرده است؛ در هر حال، فرض این مدلها به این صورت است که عاملهای تأمین کننده بدون توجه به دینامیک های زمانی بخش بازار و همچنین تأثیرات تعاملات سمت تقاضا بر تصمیمات توسعه ظرفیت یک استراتژی بلند مدت را برای توسعه ظرفیت تولید انرژی اتخاذ می کنند. در این تحقیق، یک رویکرد شبیه سازی مبتنی بر نظریه بازی ها مورد استفاده قرار گرفته است که برای توضیح مفید بودن رویکرد برنامه ریزی پیشنهادی و همچنین برای بحث درباره اثربخشی آن از یک مطالعه ی موردی (سیستم انرژی الکتریکی ایران) استفاده شده است. نتایج بدست آمده نشان دادند که رویکرد یکپارچه پیشنهادی نه تنها یک طرح توسعه تولید مقرون به صرفه تر بوده بلکه در مقایسه با رویکرد نظریه بازی طرحی سازگارتر با محیط زیست نیز ارائه می‌کند.

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